REAL-TIME ANOMALY DETECTION IN SOLAR PANEL ARRAYS: INTEGRATING SINGLE SHOT MULTIBOX DETECTOR (SSD) WITH IOT AND EDGE COMPUTING

Dr.Y.Rajendra Babu[1], *N.Indira Priyadarsini*[2], *Dr.P.G.K.Sirisha*[3], *Dr.C.Ravishankar Reddy*[4]

[1]Professor, EEE Department, Sreenidhi University, Hyderabad, Telangana, India.
[2]Assistant Professor, Department of Information Technology, Vignan Bharathi Institute of Technology, Hyderabad, Telangana, India
[3]Associate Professor, KKR & KSR Institute of Technology & Sciences, Guntur, A.P, India.
[4]Associate Professor, ECE Department, Sreenidhi University, Hyderabad, Telangana, India.

Abstract. Convolutional Neural Networks (CNNs) have revolutionized feature extraction for fault detection in solar panels by using hierarchical spatial extraction using convolutional layers These networks reveal important features such as cracks, hotspots, and internal cell anomalies while reducing redundancy. Using pre-trained algorithms such as ResNet and VGGNet enhances transfer learning and accelerates convergence, strengthens model accuracy error detection Noise filtering techniques including a Gaussian filter, mean filtering, and a Fast Fourier transform (FFT) for error detection. Eliminating image noise when storing information which is important for real-time fault detection, the Single Shot Multibox Detector (SSD) efficiently predicts bounding box-class probabilities with its multi-scale feature detection and anchor box mechanism. This simultaneous detection of faults in large solar panel arrays is possible. IoT sensors support these processes by providing real-time assessment of system integrity and environmental conditions, supported by edge computation for minimal latency fault by adaptive unsupervised learning approaches by separation forest algorithms integrated for anomaly detection. The knowledge is further enhanced by integrating these techniques. A comprehensive framework is provided for solar panel analysis, fault detection, and better performancepage margins and justified.

Keywords: CNN, Feature Extraction, Fault Detection, SSD, IoT Sensors, Anomaly Detection, Solar Panels, Machine Learning.

1 Introduction

Solar fabrication is the sequence of procedures required to produce photovoltaic (PV) panels and solar cells, therefore enabling solar energy to be harnessed and turned into electricity. Raw materials, including silicon, which is cleaned and shaped into wafers, start this process. Doping these wafers generates a p-n junction that enables the photovoltaic effect. Anti-reflective coatings are used to improve light absorption and conductive layer deposition gathers the produced electricity. Efficiency is raised using advanced manufacturing processes like multi-junction cell fabrication and thin-film deposition. Solar construction is including artificial intelligence and automation more and more to guarantee scalability and accuracy. Durable, reasonably priced, high-performance solar cells are the target. Notwithstanding its advantages, solar fabrication presents difficulties including energy-intensive manufacturing techniques and the need of sustainable recycling solutions for end-of-life PV panels.

Solar panels must have manufacturing flaws identified by CNN to ensure quality, efficiency, and life. Complex technologies, solar panels may greatly affect their performance and energy production even from little flaws like micro-cracks, scratches, or material irregularities. CNNs known for their strong feature extraction capacity can automatically find and categorise these flaws from high-resolution photos. CNNs may identify minor abnormalities perhaps undetected by conventional inspection techniques or human examination by analysing textures and patterns. While cutting inspection time and labour costs, this automated method improves detection accuracy and consistency. Early manufacturing process problem identification also enables quick remedial action, therefore reducing waste and manufacturing costs. CNN-based fault detection guarantees that only premium panels find their way to the market, therefore enhancing dependability and consumer satisfaction. By optimising the efficiency and lifetime of solar panels, using CNNs in quality control ultimately helps to further the more general objective of sustainable energy.

Solar manufacturing uses CNN extensively for defect identification and quality assurance. Still, their application has clear limits. First, CNNs need large and varied datasets to reach high accuracy, which might be difficult to find in solar manufacture, particularly for uncommon or complicated flaws. CNNs' computationally heavy training procedure sometimes calls for specialised gear like GPUs, which might raise prices. CNNs may also suffer from domain changes, in which performance may be lowered by variations in illumination, texture, or resolution between the operating and training environments. Their lack of interpretability also makes it challenging to grasp their methods of decision-making. Given the high-speed manufacturing lines in solar fabrication, real-time defect detection utilising CNNs may be difficult. The complexity is further increased by CNNs often requiring retraining and fine-tuning to respond to new fault kinds. Finally, depending on CNNs creates an artificial intelligence skill dependence that may not be easily accessible in all production environments.

There are many ways to find manufacturing flaws in solar panels, each using separate technologies and technique. Conventional techniques include EL imaging and hand visual examination wherein flaws like dormant cells and micro-cracks become apparent under certain lighting conditions. These techniques, nevertheless, are prone to human mistake and labour-intensive. Computer vision-based automated image processing methods that examine high-resolution photos for irregularities provide a more reliable and scalable solution. Particularly CNN, machine learning models have become quite effective tools as they can automatically learn and identify intricate patterns related with flaws. Another method is infrared thermography, which finds flaws by finding uneven heat patterns on the panel's surface. Multi-data source hybrid approaches using EL or infrared photography and deep learning improve accuracy. Recently developed transfer learning and GAN anomaly detection methods improve identification in difficult situations.

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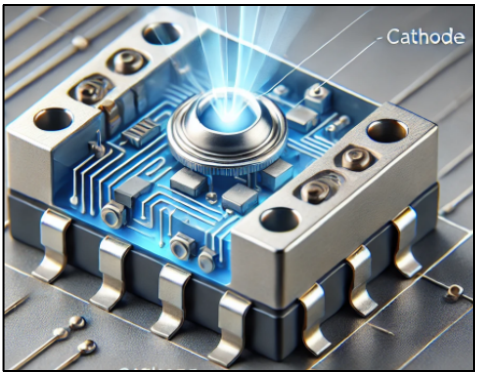
1.1 IoT Sensors Required for Solar Fabrication:

IoT sensors have been integrated into solar panels for real-time analysis and monitoring. Thermographic cameras identify thermal anomalies representing hot spots and other failures. A photodiode sensor ensures the lines operate in optimum sunlight by monitoring irradiance. Ultrasonic sensors are used to check non-destructively and to detect microcracks and fractures in the panel materials. Leakage sensors are also used, which detect mechanical stress; this gives a system a sound basis for assessing integrity. The two latter types of sensors introduced here will monitor humidity and temperature, thereby creating conditions that may affect performance during construction or operation. Smart RFID tags ensure operational life while enabling traceability and correlation of errors. Spectroscopic sensors determine the composition of the solar cells; thus, they comply with quality standards. All these kinds of research work together with edge computing devices to allow preprocessing of data and detection of anomalies right at the source, thereby minimizing latency. Internet-of-Things-enabled systems provide an integrated approach to reliability enhancement while construction as well as maintenance of solar panels.



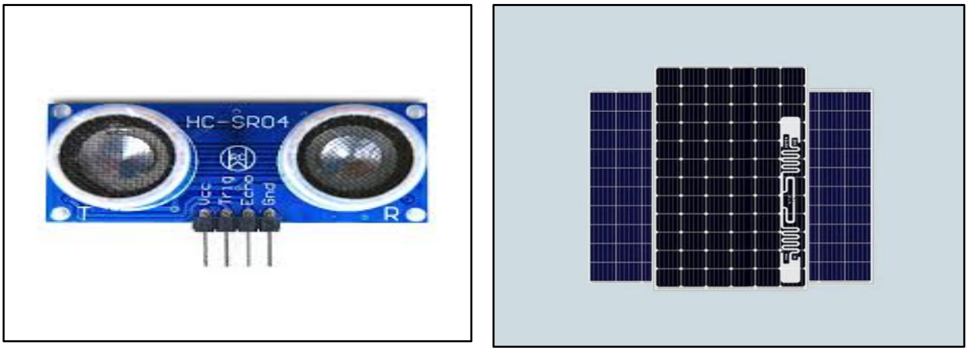


Figure 1: IoT Sensors

1.2 RCNN for Object Detection

Deep learning architecture often used in object identification applications is RCNN. Region proposal, feature extraction, and classification are three steps in which RCNN divides the object detection process. It initially creates region ideas by means of selective search, therefore spotting possible sites for things. A CNN then grabs features from these areas. At last, a classifier usually a Support Vector Machine determines whether certain items exist within every area. Advancing object identification and obtaining better accuracy than conventional techniques, RCNN has proven indispensable. RCNN may find flaws in solar cells in solar fabrication like pollution, discolourations, or fractures. Although the design is computationally cheap since each area suggestion must be independently processed, which renders it inappropriate for real-time applications despite its correctness. Faster variations of RCNN that solve efficiency issues like Fast RCNN & Faster RCNN have influenced each other.

Although RCNN is a strong object detection framework, it has some shortcomings. Its computational inefficency is the most important disadvantage. Because it takes a long time to make region suggestions and identify each one separately, RCNN isn't recommended for real-time situations or situations where computing capacity is limited. Comprising many phases fine-tuning the CNN, training a SVM, & honing bounding box regressors the training method is likewise time-consuming and difficult. For training, RCNN needs a lot of labelled data, which may be costly and time-consuming to acquire in specialised uses like solar manufacturing. Furthermore slower than its predecessors, Fast RCNN and Faster RCNN, RCNN depends on region proposal methods, such as selective search. Its lack of adaptability in managing overlapping objects or occlusions adds even another restriction that could cause false positives or missing detections. These restrictions have motivated the creation of object detecting more effective models.

1.3. Anomaly Detection:

In solar fabrication, anomaly detection is the identification of flaws or deviations from the high-quality solar cell standard patterns. Usually, the process begins with data collection, which involves gathering manufacturing line photos or sensor readings. Then this data is analysed using advanced methods like computer vision & ML. Common flaws that could greatly affect solar cell performance include microcracks, discolourations, and surface pollution. Deep learning algorithms especially are taught to identify regular patterns and aberrations in machine learning models. Common utilised techniques include unsupervised approaches like autoencoders or CNNs. By use of anomaly detection systems, real-time monitoring is made possible and the chance of faulty goods finding their way to the market is reduced. Dealing with noisy data, attaining high detection accuracy, & adjusting to new fault kinds provide difficulties in this procedure. Automation for anomaly detection guarantees not just high quality products but also improves manufacturing productivity and lowers expenses.

1.4. Different Types of Anomaly Detection:

Anomaly detection in data analysis is the identification of occurrences, trends, or data points Anomaly detection in data analysis is the deviating greatly from predicted values. Manufacturing, fraud detection, healthcare, & cybersecurity are just a few of the many disciplines where it finds extensive use. One may generally classify the approaches for anomaly detection into statistical, ML, & DL ones. Statistical approaches depend on presumptions of the underlying data distribution. Often utilised are methods include Chauvenet's criteria, Grubbs' test, and Z-score. They find anomalies by gauging how much data points stray from statistical norms like the mean or standard deviations. These straightforward, understandable techniques struggle with complicated, high-dimensional, or non-Gaussian datasets even if they are interpretable. These approaches group data points using clustering techniques as K-Means or DBSCAN. Anomalies are found as spots outside of any cluster or distant from cluster centroids.

These techniques are useful for unsupervised anomaly identification but need careful parameter tuning that is, with regard to cluster count or density criteria. These distance-based techniques such as k-NN calculate the distance between data points. Points distant from their closest neighbours are noted as oddities. For small datasets, they perform well; yet, for big or high-dimensional data they are computationally costly. Density-Based Strategies Techniques meant to find anomalies depending on data density include Isolation Forest and LOF. LOF finds places in low-density areas that are not normal and labels them as anomalies. Isolation Forest, on the other that point, separates anomalies by dividing the dataset over and over again. These methods fit and are effective for big datasets. Combining many approaches may improve detection accuracy. Combining density-based approaches with clustering, for instance, may take use of their respective advantages.

2. LITERATURE SURVEY:

Dai Qin et al [1] By using an improved CNN design, fault identification in photovoltaic panels may be substantially improved. Taking into account the significant part that photovoltaic (PV) power production plays in the process of reaching carbon neutrality, it highlights the need of effective defect identification in order to guarantee both reliability and efficiency. Enhancing feature extraction, particularly for irregular defects such as linear fractures, is the goal of the proposed technique, which incorporates adaptive dimensional feature aggregation via the combination of DCN & C3 convolutional layers. It adds a CoTAttention & a CAM to enhance the identification of minor flaws and effective allocation of computing resources. This method fixes slow convergence and makes it more stable by using Focal-EIoU as the loss function. The objective of this all-encompassing strategy is to obtain a greater detection accuracy, which will eventually lead to an improvement in the quality of PV panels and assist activities pertaining to sustainable energy.

Hiren Mewada et al [2] have found an issue in PV solars by utilizing the EL to analyze with DCNN methodology. Identification of different damages in the tool will leads to loss of person interest to purchase the tool so, before delivering the product provider should check mircro-cracks, hotspot etc. The main issue occur during was less clarity and noise in EL images to find the defects. By simplifying the xception network like adding convolution layer and dropout for stopping it for arrange it well. Along CNN was introduced to enhance EL images, like rotating and shifting the dimensionality to arrange the dataset more even. The model can be arranged into couple of groups working and not. Here are some ways that automatic problem-finding can help make solar panels work better, last longer, and get more individuals to use renewable energy sources.

Langyue Zhao et al [3] identification of flaw PV cells is essential task to overcome the efficiency of solar energy. Main issue occurred while solar panels are not solved with traditional technique which may last with small flaws even predicted. Based on two requirement extraction of features and parallel transformation was designed a new technique known as PD-DETR. By splitting the frequency and fine features a hybrid model is generated. This features works efficiently by identifying the defected part easily and makes computer to work less-harder. In contrast to high-frequency features, which collect information about contours, fine features are able to identify faults that are very little but yet significant. During training, the encoder and decoder are able to learn more effectively because to the PD-DETR's concurrent Faster R-CNN recognition heads. In situations when there is insufficient monitoring, this resolves the issues that arise with the models that are currently in use. Furthermore, training is more precise and quicker because to the one-to-many matching structure. The proposed system can evaluate data in real-time and switch DETR versions while discovering minute defects in complex backdrops.

Ashwini Raorane et al [4] has developed a optimized method to detect the damaged photovoltaic panels which many have spot issues as major defect. This panels have issues such as spikes or watts differences which may leads to loss of power and efficiency in system. Initial stage includes pre-processing which leads to cleaning and get rid of noises. After the data was processed three features are combined those are LBP, LOOP, and LDP. By combining the outcome of these features are converted to vectors and transmitted to CNN classifier which was optimized with novel approach AqWh, which was known as Aquila and Wild Horse optimization approach. Therefore, this improves the CNN methodology faster and accurate the performance. To localise the flaws VGG16 was utilized in single, multiple or string hotspots. Providing a powerful method for the protection and upkeep of photovoltaic plants, this combination model emphasises on improving the efficiency of categorisation and targeting.

Yuqi Liu et al [5] using DL to build ASDD-Net, a system for finding flaws in pictures of polycrystalline silicon solar cells that glow in the dark. Finding flaws in these kinds of cells is hard because their crystal structures are complicated and they have flaws at different sizes. ASDD-Net has some cool new features, like the SPD module, that make it easier to find small problems while keeping small details when downsampling. The EC2f and HAC3 units are also used for feature fusion and flexible focus processes that help see defects better. The MobileViT_CA module improves the merging of global and local features, which makes multi-scale recognition more accurate. Detection accuracy and processing speed are both taken into account by the design, which combines neural and transformer methods. These improvements fix problems like different kinds of defects, complicated backgrounds, and losing small features. They provide a strong way to find and sort defects in real time in industrial solar applications.

Table 1: Existing System Analysis

Author	Algorithm	Merits	Demerits	Accuracy
Dai Qin et al	C3_DCN, CNN	By combining DCN and C3 has increased the performance.	The performance differences was less when before and after improvement were done.	91.8%
Hiren Mewada et al	Xception, Deep CNN	By simplifying the xception low clarity issues are solved.	Multi-class classification was not performed at a time.	94.3%
Langyue Zhao et al	Fast R-CNN, PD-DETR	During training itself the encoder and decoders are worked.	Automatic parameters are not set.	64.8 - epochs
Ashwini Raorane et al	AqWh, CNN, Vgg16	By combining three pattern an optimization was generated to CNN. A approach was designed for appropriate performance.	Need to improve effectiveness.	98.5%
Yuqi Liu et al	ASDD-Net	Fusion features and adaptive mechanisms are efficiently derived.	Segmentation methods can be utilized for improving the methods.	92.3% - precision

3. PROPOSED METHODOLOGY:

3.1. Removal of Noisy Data: Denoising data from solar instrument imaging increases accuracy by filtering out distortions introduced during image acquisition or preprocessing. Noise in images can be caused by environmental factors, sensor artifacts, or compression. In numerical terms, techniques such as Gaussian filters are used to smooth pixel intensity variations by using the convolution function of the Gaussian kernel equation (1)

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \text{ - (1)}$$

in particular, where σ determines the smoothness, and (x, y) represent pixel coordinates. Alternatively, Median filtering eliminates noise by replacing the value of a pixel with its nearest median value, preserving edges. Two-dimensional filters, including spatial intensity-field information, strike a good balance between edge noise removal and edge preservation. Fast Fourier transform (FFT) techniques can also eliminate target noise frequencies. Together, these statistical methods ensure the conservation of important features and eliminate unwanted features that are critical for reliable error detection.

3.2. CNN to Extract Features: Feature extraction with Convolutional Neural Networks (CNNs) requires the use of deep learning architectures to identify and reduce significant features in solar panel images CNNs use convolutional levels, which use filters for spatial extraction hierarchy from the data, such as cracks, hotspots, or color changes in photovoltaic internal cells Provides visualization which is important To reduce redundant data and highlight important features Input image goes through multiple layers including convolution, pooling, and activation functions. Activation functions like ReLU ensure single dimensionality and increase the model's ability to detect complex patterns. Max pooling layers decreases the size of activation maps, reducing dimensionality while preserving key features. Using pre-trained models such as ResNet, Inception, or VGGNet, transfer learning can be used to speed up convergence and improve accuracy in fault detection tasks Feature extraction through CNNs ensures robust information and observations of different track faults over detection.

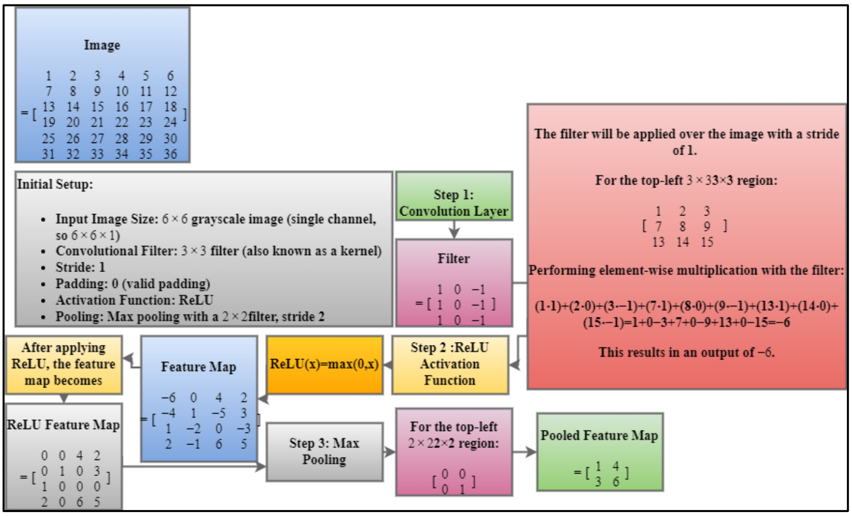


Figure 2: Mathematical Representation of Feature Extraction using CNN

3.3. SDD Object Detection Process: The Single Shot Multibox Detector (SSD) is an advanced object detection system optimized for real-time applications. The SSD works by predicting bounding box and class likelihoods straight from the activation maps in the CNN without the need for a separate area proposal network. It uses a multi-scale feature recognition strategy, which enables the detection of features in different sizes. The process begins by extracting feature maps from a backbone network, such as

MobileNet or VGG, followed by the use of multiple convolution layers to detect objects at different scales Search each layer for pre-defined, executed boxes the previously defined features and sizes of Non-maximum suppression (NMS) are used to extract the overlapping boxes against which the highest confidence scores from there. SSD combines hard negative mining to address skewed distribution between positive and negative instances, ensuring robust learning. The efficiency and accuracy of the construction justifies the detection of defects such as cracks or hot spots in expansive solar panels.

In fault detection, the SSD uses a unique algorithm that optimizes speed and accuracy. Using convolutional feature layers of varying depth, the framework captures finer details at higher resolution levels and broad contextual information at lower resolution The training set includes loss functions such as smooth L_1 loss for localization and softmax for classification bounding accurate box forecasts and accurate classification of faults Ensure that the anchor-box mechanism used in an SSD matches forecasts to ground truth to account for scale-aspect ratio variations, which is important for fault localization Data enhancement techniques including random crop, flipping, and color adjustment further improve model robustness to image conditions Multiclass predictions simultaneously Ability to The SSD's control capabilities make it easy to detect multiple errors in a single scan. This scalability and adaptability highlights its suitability for large-scale solar panel monitoring and fault detection.

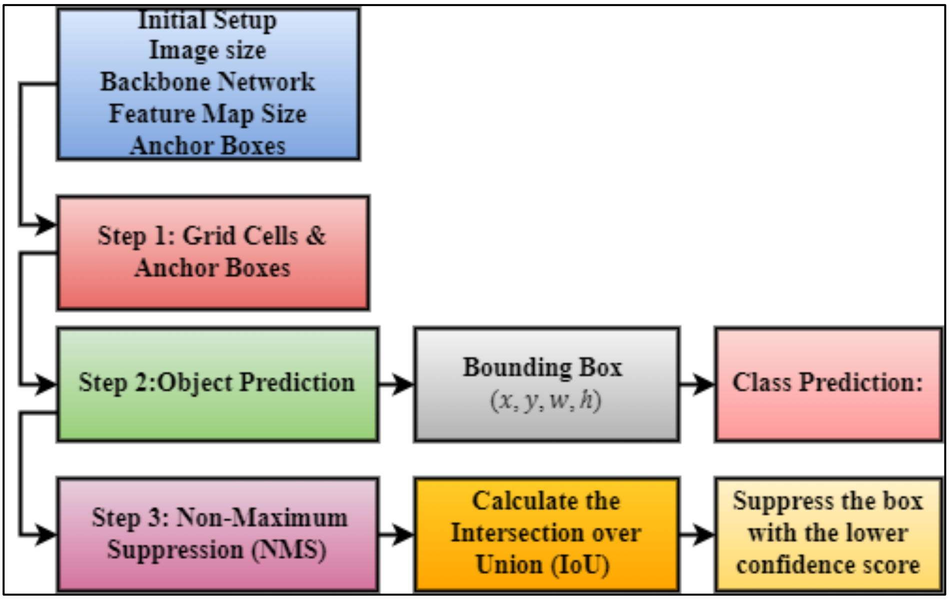


Figure 3: Working of SDD Algorithm

3.4. Isolation Forest for Anomaly Detection: An unsupervised machine learning method used in anomaly identification is the Isolation Forest approach. Isolation Forest focusses on spotting anomalies by separating data points that stray far from the norm, unlike conventional clustering techniques. It divides features to create random decision trees and counts the splits needed to separate every data point. Being uncommon and unique, anomalies need less splits to be isolated, so their typical path lengths are less.

This method is computationally efficient and especially useful for high-dimensional datasets, which qualifies for large-scale uses like solar manufacture. Versatile as the Isolation Forest does not presuppose any previous distribution of data and is strong against noise. In solar fabrication, it may spot flaws in solar cells or inconsistent manufacturing trends in data. To get best results, nevertheless, its performance relies on the selected settings and can need adjustment. Industrial anomaly detection projects often use the straightforward and effective method of the algorithm.

The separation forest algorithm is a very effective approach in identifying anomalies, or faults, within solar power plants. In this case, an unsupervised machine learning technique eliminates the anomalies by creating a decision tree that further splits the data. The algorithm operates on the assumption that anomalies have few separations because of their rareness and peculiar characteristics. It captures data points as nodes in the tree structure and computes the distance needed to separate each point. The anomaly score is represented by the average long path, whereas short paths are considered outliers. For mathematical purposes, inverse scoring is given as equation (2)

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} - (2)$$

where $h(x)$ is the distance, $c(n)$ is the scaling constant, and n is the sample size. Effective and adaptive statistics of separation forest for processing big data like thermal images or electrical measurements Adaptation of model to different fault characteristics ensures accurate anomaly detection, thereby facilitating proactive maintenance and operational risk reduction.

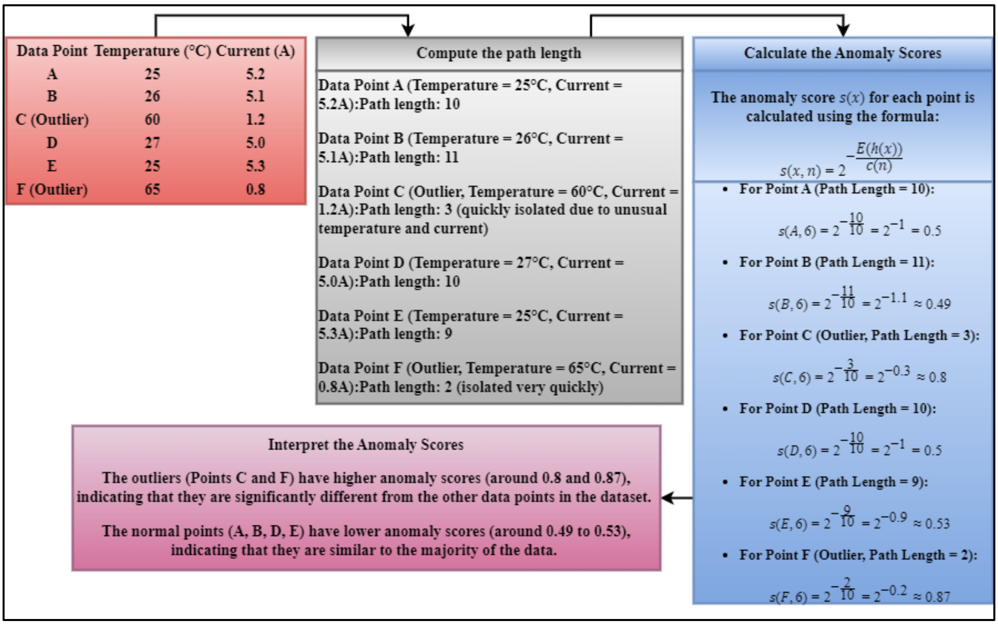


Figure 4: Working of Isolation Forest Algorithm for Anomaly Detection

4. RESULTS & DISCUSSION

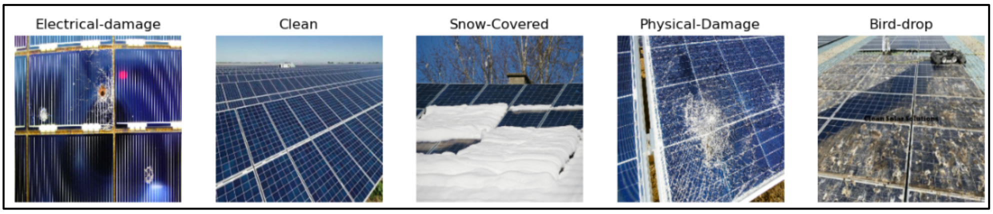


Figure 5: Identification of Defects in Solar Panels

Figure 5 presents the state of the solar panel by using the proposed algorithm. It can predict the 5 states of the solar panel. Thermal imaging and electroluminescence testing can identify internal flaws that cause electrical damage, such as bad soldering, reverse bias, or short circuits, which result in hotspots, decreased efficiency, and safety hazards. By permitting maximum solar absorption, clean panels guarantee optimal performance, which can be attained through routine maintenance and sensor monitoring. Tilt designs, heating systems, or automated cleaning robots can prevent snow-covered panels from blocking sunlight, which lowers efficiency and creates unequal stress. Physical damage that may be seen by visual inspections and electroluminescence, such as cracks caused by hail, debris, or wear, interferes with the flow of light and electricity. Bird droppings produce localized shadowing, which lowers power output and results in hotspots. Cleaning systems, hydrophobic coatings, and anti-bird meshes are among remedies. These problems demonstrate the significance of observation and upkeep to guarantee solar panel effectiveness and durability

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Epoch 5/15
23/23 [==============================] - 10s 337ms/step - loss: 0.0682 - accuracy: 0.9788 - val_lo
ss: 0.7279 - val_accuracy: 0.8079
Epoch 6/15
23/23 [==============================] - 10s 326ms/step - loss: 0.0830 - accuracy: 0.9788 - val_lo
ss: 0.7652 - val_accuracy: 0.8305
Epoch 6: early stopping
```

Figure 6: Training Log Details

The model's performance over epochs is displayed in the figure 6, which also highlights measures like validation accuracy, loss, and accuracy. By epoch 6, the validation accuracy had improved to 83.05% from 80.79% at epoch 5. But after epoch 6, early halting was initiated, most likely because, in spite of the improvement in validation accuracy, the validation loss either stopped improving or got worse. When a model performs better on the training set but is unable to generalize further on the validation set, it may have begun overfitting. Optimizing the learning rate or fine-tuning factors like the early halting mechanism's patience may assist improve performance.

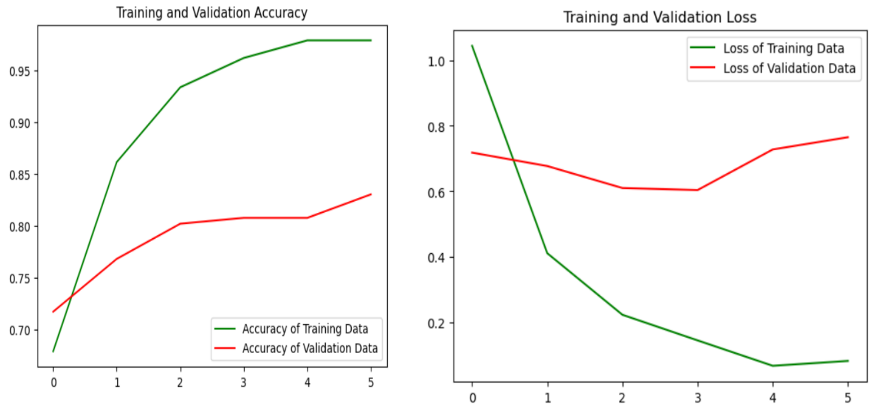

Figure 8: Metric Evaluation of Proposed Model

The model's training performance is depicted in the figure 8. While validation accuracy first rises but then plateaus, the accuracy plot demonstrates that training accuracy climbs gradually and approaches 100%. This suggests that the model is learning but may have trouble generalizing further. Effective learning on the training set is seen in the loss plot, where training loss steadily declines. But after initially declining, validation loss continues to increase, indicating the beginning of overfitting, a process in which the model performs better on the training set but deteriorates on unseen data. In order to enhance generalization, this implies that regularization strategies like dropout or early halting are required.

5. CONCLUSION

The combination of advanced machine learning techniques and IoT-based monitoring has dramatically improved the fault detection and reliability of solar panel systems. CNN enables the extraction of important features from complex datasets and ensures detection of complex and accurate defects. Techniques such as Gaussian filtering and FFT denoising remove distortion and preserve important image features, providing clean data for analysis. SSD has proven to be effective in detecting multiple defects simultaneously with its innovative anchor box mechanism and hard negative mining, making it scalable for large-scale applications well-defined with IoT sensors. This system is enhanced by real-time analysis of the efficiency increased with anomaly detection, while edge computing reduces data processing latency. Isolated forests with infrequent and robust anomaly detection provide the best solutions for projected runoff and risk mitigation. Together, these methods ensure that the solar panel systems are reliable and efficient, support proactive maintenance procedures, extend their service life, and reduce downtime.

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